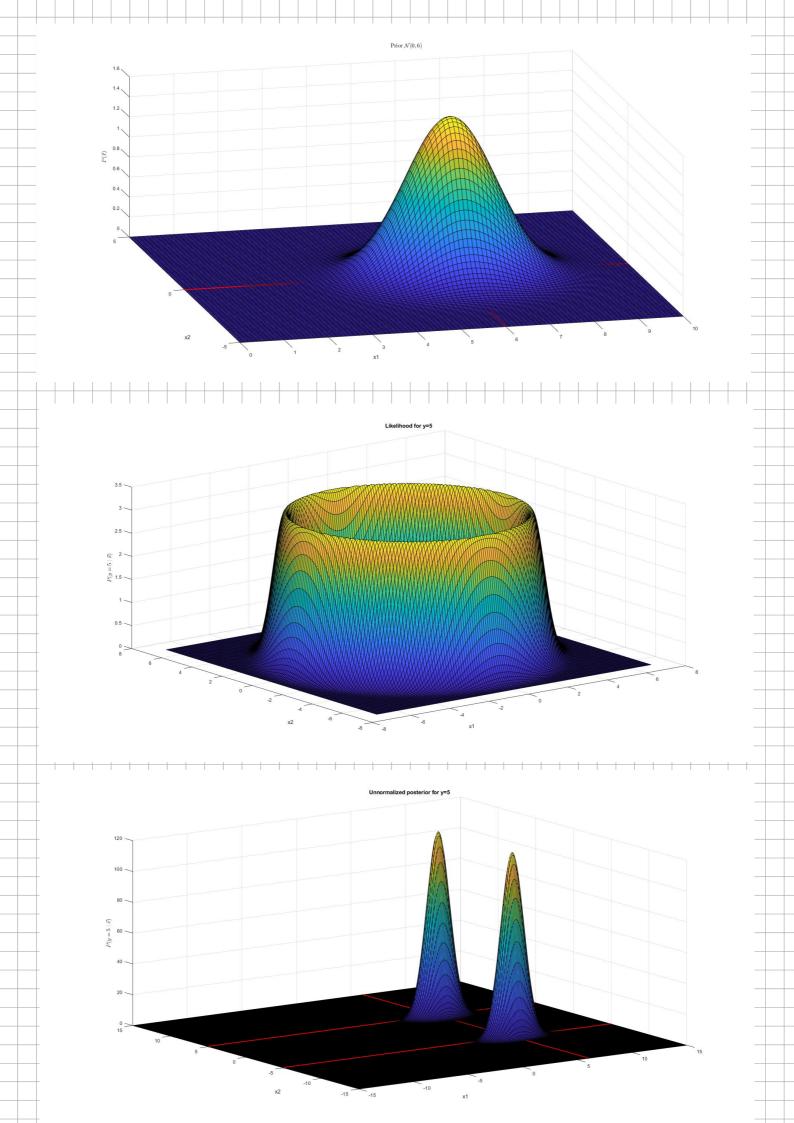
TM- Exercise 2 2.1 (a) The function & (x)= \x, 2 + x2 is mt invertible since it is not insection; it's a projection from a 2D space to 10 space. (b) y - \x 2 + \x 2 + \x 2 + \x 2 - \x 1 + \x 2 - \x  $(C) Y = 5 , \rho(X) = 1$ 3 ang max P(41X). 1 = ang max 2 . cxp (-(Ux12 + X22 - 5) -) max  $\int_{9}^{9} \sqrt{1 + x_2^2} = 5$  -)  $x_1^2 + x_2^2 = 25$ mex value for all pairs of (x, xz) sitting on the circle contered in 0 with ralius 5 (d)



(P) 
$$\rho(X|Y=5) \propto \rho(Y=5|X) \rho(X) = \frac{1}{2\pi} (x - \rho(-2(\sqrt{x_1^2 + x_1^2} - s)^2).$$
 $\frac{1}{2\pi} \cdot \exp(-(x - \mu_1)^2 + x^2 - x - \mu_1)) = \frac{1}{2\pi} (x - \mu_1)^2 + x_1^2.$ 
 $\frac{1}{2\pi} \cdot \exp(-(x - \mu_1)^2 + x^2 - x - \mu_1)) = \frac{1}{2\pi} (x - \mu_1)^2 + x_1^2.$ 
 $\frac{1}{2\pi} \cdot \exp(-(x - \mu_1)^2 + x^2 - x - \mu_1)) = \frac{1}{2\pi} (x - \mu_1)^2 + x_1^2.$ 
 $\frac{1}{2\pi} \cdot \exp(-(x - \mu_1)^2 + x^2 - x - \mu_1)) = \frac{1}{2\pi} (x - \mu_1)^2 + x_1^2.$ 
 $\frac{1}{2\pi} \cdot \exp(-(x - \mu_1)^2 + x^2 - x - \mu_1)) = \frac{1}{2\pi} (x - \mu_1)^2 + x_1^2.$ 
 $\frac{1}{2\pi} \cdot \exp(-(x - \mu_1)^2 + x - x - \mu_1) = \frac{1}{2\pi} (x - \mu_1)^2 + x_1^2.$ 
 $\frac{1}{2\pi} \cdot \exp(-(x - \mu_1)^2 + x - \mu_1) = \frac{1}{2\pi} (x - \mu_1)^2 + x_1^2.$ 
 $\frac{1}{2\pi} \cdot \exp(-(x - \mu_1)^2 + x - \mu_1) = \frac{1}{2\pi} (x - \mu_1)^2 + x_1^2.$ 
 $\frac{1}{2\pi} \cdot \exp(-(x - \mu_1)^2 + x - \mu_1) = \frac{1}{2\pi} (x - \mu_1)^2 + x_1^2.$ 
 $\frac{1}{2\pi} \cdot \exp(-(x - \mu_1)^2 + x - \mu_1) = \frac{1}{2\pi} (x - \mu_1)^2 + x_1^2.$ 
 $\frac{1}{2\pi} \cdot \exp(-(x - \mu_1)^2 + x - \mu_1) = \frac{1}{2\pi} (x - \mu_1)^2 + x_1^2.$ 
 $\frac{1}{2\pi} \cdot \exp(-(x - \mu_1)^2 + x - \mu_1) = \frac{1}{2\pi} (x - \mu_1)^2 + x_1^2.$ 
 $\frac{1}{2\pi} \cdot \exp(-(x - \mu_1)^2 + x - \mu_1) = \frac{1}{2\pi} (x - \mu_1)^2 + x_1^2.$ 
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 $\frac{1}{2\pi} \cdot \exp(-(x - \mu_1)^2 + x - \mu_1)^2 + x_1^2.$ 
 $\frac{1}{2\pi} \cdot \exp(-(x - \mu_1)^2 + x - \mu_1)^2 + x_1^2.$ 
 $\frac{1}{2\pi} \cdot \exp(-(x - \mu_1)^2 + x - \mu_1)^2 + x_1^2.$ 
 $\frac{1}{2\pi} \cdot \exp(-(x - \mu_1)^2 + x - \mu_1)^2 + x_1^2.$ 
 $\frac{1}{2\pi} \cdot \exp(-(x - \mu_1)^2 + x - \mu_1)^2 + x_1^2.$ 
 $\frac{1}{2\pi} \cdot \exp(-(x - \mu_1)^2 + x - \mu_1)^2 + x_1^2.$ 
 $\frac{1}{2\pi} \cdot \exp(-(x - \mu_1)^2 + x - \mu_1)^2 + x_1^2.$ 
 $\frac{1}{2\pi} \cdot \exp(-(x - \mu_$ 

#### **Table of Contents**

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# b) Generating the inputs with the generative model for the three level HGF

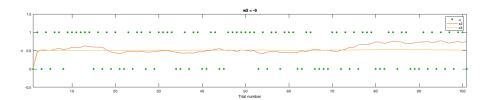
```
k2 = 1;
w2 = -4;
w3 = -6;
x3 init = 0;
x2_init = 0;
u init = 0;
inputs = generate_inputs(k2,w2,w3,x3_init,x2_init,u_init);
u = inputs(:,1);
x2 = inputs(:,2);
x3 = inputs(:,3);
scrsz = get(0,'ScreenSize');
outerpos = [0.2*scrsz(3),0.7*scrsz(4),0.8*scrsz(3),0.3*scrsz(4)];
figure('OuterPosition', outerpos)
plot(u, '.', 'Color', [0 0.6 0], 'MarkerSize', 11)
xlabel('Trial number')
ylabel('u')
axis([1, length(inputs), -0.1, 1.1])
hold on;
plot(x2);
plot(x3);
legend('u','x2','x3')
str = sprintf('k2= %0.5g, w2= %0.5g, w3 = %0.5g, x3_init= %0.5g,
x2_init = %0.5g, u_init= %0.5g', k2,w2,w3,x3_init,x2_init,u_init);
title(str)
hold off;
```

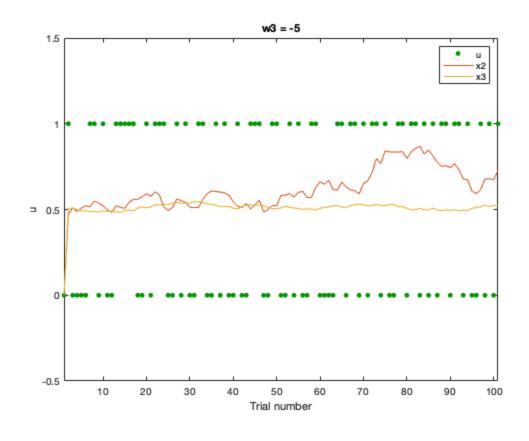
## Trying out different thetas

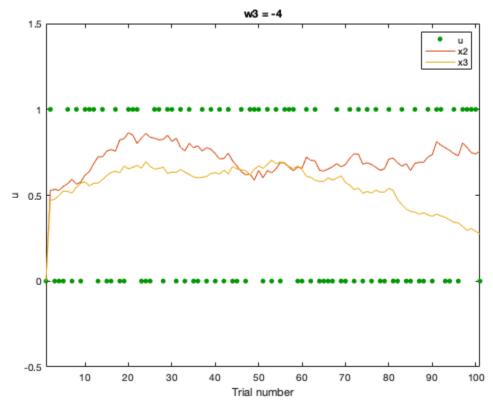
Higher volatility coefficients make the generated x2 and x3 much more variant. If it is too low, x2 (the tendency towards 1) becomes constant

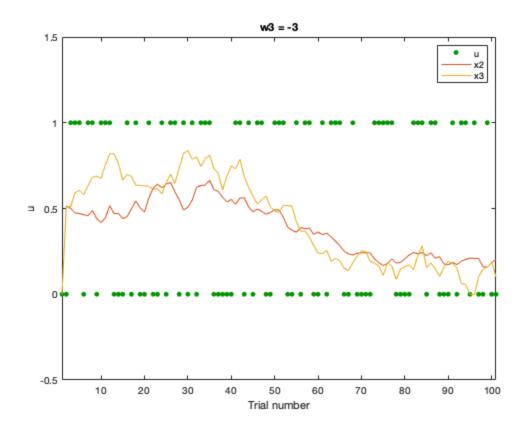
k2 = 1;

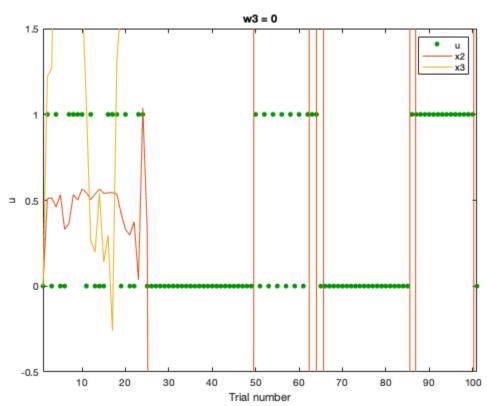
```
w2 = -4;
w3_{list} = [-6, -5, -4, -3, 0, 1];
x3_{init} = 0.5;
x2 init = 0.5;
u_init = 0;
it = 1;
for w3 = w3_list
inputs = generate_inputs(k2,w2,w3,x3_init,x2_init,u_init);
u = inputs(:,1);
x2 = inputs(:,2);
x3 = inputs(:,3);
figure(it)
plot(u, '.', 'Color', [0 0.6 0], 'MarkerSize', 11)
xlabel('Trial number')
ylabel('u')
axis([1, length(inputs), -0.5, 1.5])
hold on;
plot(x2);
plot(x3);
legend('u','x2','x3')
str = sprintf('w3 = %d', w3);
title(str)
hold off;
it = it + 1;
end
```

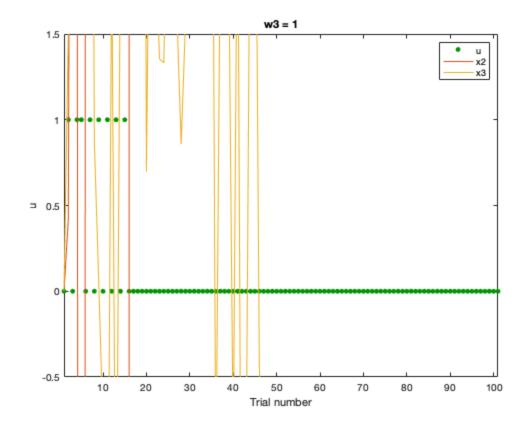








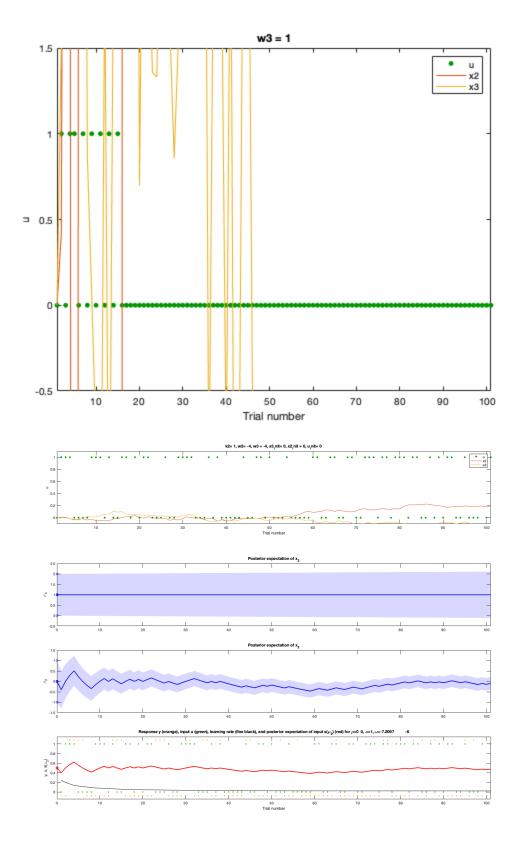




## c) Simulating beliefs and responses

```
%The estimates for w2 and w3 (-7.2097, -6.0000) are far of the
 original values (-4,
%-4).
%The simulated agent does not track well x3 (which is estimated
 constant at 1 but is in fact variant around 0), nor x2. In our
 simulation x2 varies between 0 and 0.2 while the agent estimates the
x2 between -0.5 and 0.5.
addpath('../tapas/HGF')
k2 = 1;
w2 = -4;
w3 = -4;
x3 init = 0;
x2 init = 0;
u_init = 0;
inputs = generate_inputs(k2,w2,w3,x3_init,x2_init,u_init);
u = inputs(:,1);
x2 = inputs(:,2);
x3 = inputs(:,3);
scrsz = get(0,'ScreenSize');
outerpos = [0.2*scrsz(3),0.7*scrsz(4),0.8*scrsz(3),0.3*scrsz(4)];
figure('OuterPosition', outerpos)
```

```
plot(u, '.', 'Color', [0 0.6 0], 'MarkerSize', 11)
xlabel('Trial number')
ylabel('u')
axis([1, length(inputs), -0.1, 1.1])
hold on;
plot(x2);
plot(x3);
legend('u','x2','x3')
str = sprintf('k2= %0.5g, w2= %0.5g, w3 = %0.5g, x3_init= %0.5g,
x2_init = %0.5g, u_init= %0.5g', k2,w2,w3,x3_init,x2_init,u_init);
title(str)
hold off;
est = tapas_fitModel([],...
                         'tapas_hgf_binary_config',...
                         'tapas_bayes_optimal_binary_config',...
                         'tapas_quasinewton_optim_config');
sim = tapas_simModel(u,...
                      'tapas_hgf_binary',...
                     [NaN 0 1 NaN 1 1 NaN 0 0 1 1 NaN
 est.optim.final(13) est.optim.final(14)],...
                     'tapas_unitsq_sgm',...
                     5,...
                     12345);
tapas_hgf_binary_plotTraj(sim)
Ignored trials: none
Irregular trials: none
Optimizing...
Calculating the log-model evidence (LME)...
Results:
Parameter estimates for the perceptual model:
    mu_0: [NaN 0 1]
    sa_0: [NaN 0.1000 1]
     rho: [NaN 0 0]
      ka: [1 1]
      om: [NaN -7.2097 -6.0000]
Model quality:
    LME (more is better): -72.0156
    AIC (less is better): 145.609
    BIC (less is better): 150.8393
    AIC and BIC are approximations to -2*LME = 144.0313.
Ignored trials: none
```



close all



#### **Task 2.3**

#### **Table of Contents**

Warning: Name is nonexistent or not a directory: /Users/Hendrik/Documents/MATLAB/TNU/Exercise2/tapas/HGF

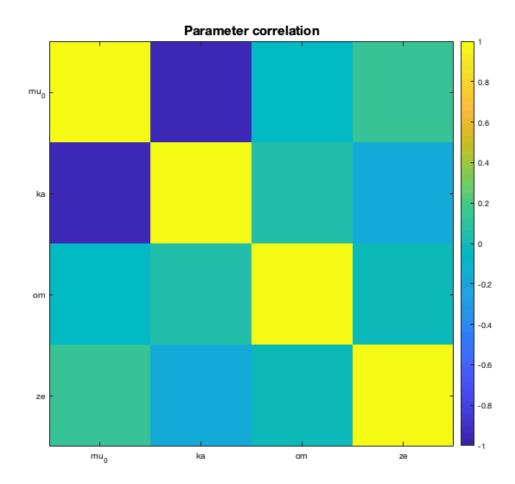
### a)k2=2.5, w2=-4, w3=-6, mu3=1, sa3=1, ze =5

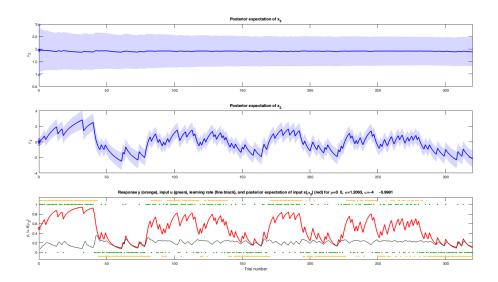
```
% The \omega_3 is very accurate in all our results.
% The estimated parameters are not as accurate as the set ones since
% variance is not zero. For example the \kappa_2 is not accurate when
% estimate it but nearly 2.5 when not estimating this parameter.
% The first covariance plot shows large correlation between \kappa_2
and
% \mu_0.
% The second covariance plot shows large correlation between \omega 2
and
% \mu 0.
%simulate model
sim = tapas_simModel(u,...
'tapas_hgf_binary',...
[NaN 0 1 NaN 1 1 NaN 0 0 1 2.5 NaN -4 -6],...
'tapas_unitsq_sgm',...
5);
%estimate param: (ze,mu3,K2,exp(w3))
est1 = tapas_fitModel(sim.y,...
```

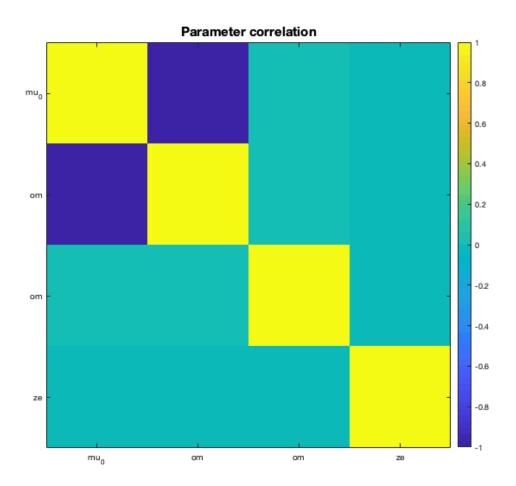
```
sim.u,...
                    'tapas hqf binary confiq 2',...
                    'tapas_unitsq_sgm_config',...
                    'tapas_quasinewton_optim_config')
%plot posterior correlation
tapas_fit_plotCorr(est1)
%plot trajectories
tapas_hgf_binary_plotTraj(est1)
%estimate param: (ze,mu3,w2,exp(w3))
est2 = tapas_fitModel(sim.y,...
                    sim.u,...
                    'tapas_hgf_binary_config_3',...
                    'tapas_unitsq_sgm_config',...
                    'tapas_quasinewton_optim_config')
%plot posterior correlation
tapas_fit_plotCorr(est2)
%plot trajectories
tapas_hgf_binary_plotTraj(est2)
응응
Ignored trials: none
Ignored trials: none
Irregular trials: none
Optimizing...
Calculating the log-model evidence (LME)...
Results:
Parameter estimates for the perceptual model:
   mu_0: [NaN 0 1.9604]
   sa_0: [NaN 0.1000 1]
    rho: [NaN 0 0]
     ka: [1 1.2063]
     om: [NaN -4 -5.9981]
Parameter estimates for the observation model:
   ze: 7.1749
Model quality:
   LME (more is better): -48.0735
   AIC (less is better): 90.2843
```

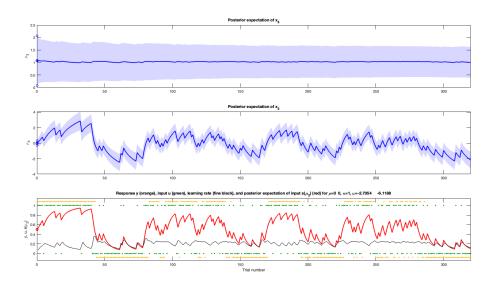
```
BIC (less is better): 105.3576
    AIC and BIC are approximations to -2*LME = 96.1471.
est1 =
  struct with fields:
        y: [320×1 double]
        u: [320×1 double]
      ign: []
      irr: [0x1 double]
    c_prc: [1x1 struct]
    c_obs: [1x1 struct]
    c_opt: [1×1 struct]
    optim: [1x1 struct]
    p_prc: [1x1 struct]
    p_obs: [1x1 struct]
     traj: [1x1 struct]
Ignored trials: none
Irregular trials: none
Optimizing...
Calculating the log-model evidence (LME)...
Results:
Parameter estimates for the perceptual model:
    mu_0: [NaN 0 1.0747]
    sa_0: [NaN 0.1000 1]
     rho: [NaN 0 0]
      ka: [1 1]
      om: [NaN -2.7054 -6.1188]
Parameter estimates for the observation model:
    ze: 7.1569
Model quality:
    LME (more is better): -48.1332
    AIC (less is better): 90.281
    BIC (less is better): 105.3543
    AIC and BIC are approximations to -2*LME = 96.2663.
est2 =
  struct with fields:
        y: [320 \times 1 double]
```

```
u: [320×1 double]
ign: []
irr: [0×1 double]
c_prc: [1×1 struct]
c_obs: [1×1 struct]
c_opt: [1×1 struct]
optim: [1×1 struct]
p_prc: [1×1 struct]
p_obs: [1×1 struct]
traj: [1×1 struct]
```









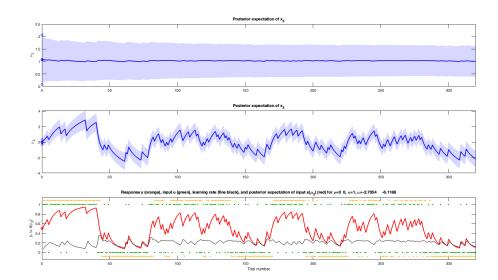
# b)k2=1, w2=-4, w3=-4.1674, mu3=2.5, sa3=6.25, ze = 5

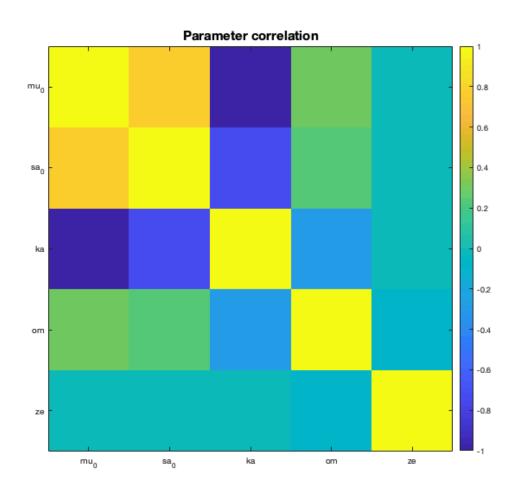
```
% The \omega_3 is very accurate in all our results.
% The estimated parameters are not as accurate as the set ones since
the
% variance is not zero. For example the \kappa_2 is not accurate when
% estimate it but equal to 1 when not estimating it.
% The estimates for \zeta and \theta are more accurate in b) than in
% We think a possible explanation for the better estimates is that the
% volatility coeffitient \theta is higher and therefore the model is
more
% flexible
% The first covariance plot shows large correlation between \kappa_2
and
% \mu 0.
% The second covariance plot shows large correlation between \omega_2
and
% \mu_0.
%simulate model
sim2 = tapas_simModel(u,...
'tapas_hgf_binary',...
[NaN 0 2.5 NaN 1 6.25 NaN 0 0 1 1 NaN -4 -4.1674],...
'tapas_unitsq_sgm',...
5);
%estimate model
est3 = tapas_fitModel(sim2.y,...
```

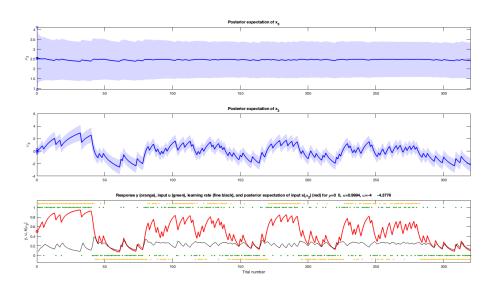
```
sim2.u,...
                     'tapas hqf binary confiq 4',...
                     'tapas_unitsq_sgm_config',...
                     'tapas_quasinewton_optim_config')
%plot posterior correlation
tapas_fit_plotCorr(est3)
%plot trajectories
tapas_hgf_binary_plotTraj(est3)
%estimate model
est4 = tapas_fitModel(sim2.y,...
                     sim2.u,...
                     'tapas_hgf_binary_config_5',...
                      'tapas_unitsq_sgm_config',...
                     'tapas_quasinewton_optim_config')
%plot posterior correlation
tapas_fit_plotCorr(est4)
%plot trajectories
tapas_hgf_binary_plotTraj(est4)
Ignored trials: none
Ignored trials: none
Irregular trials: none
Optimizing...
Calculating the log-model evidence (LME)...
Results:
Parameter estimates for the perceptual model:
    mu_0: [NaN 0 2.5364]
    sa_0: [NaN 0.1000 2.5626]
     rho: [NaN 0 0]
      ka: [1 0.9994]
      om: [NaN -4 -4.3776]
Parameter estimates for the observation model:
    ze: 4.7421
Model quality:
    LME (more is better): -67.6089
    AIC (less is better): 130.7859
    BIC (less is better): 149.6275
    AIC and BIC are approximations to -2*LME = 135.2177.
```

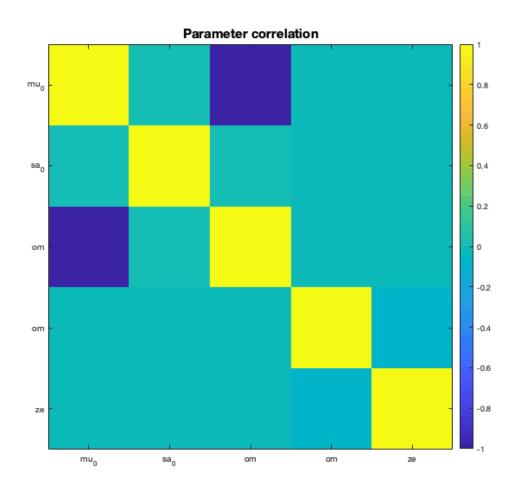
```
est3 =
  struct with fields:
        y: [320 \times 1 double]
        u: [320×1 double]
      ign: []
      irr: [0×1 double]
    c_prc: [1x1 struct]
    c_obs: [1x1 struct]
    c_opt: [1x1 struct]
    optim: [1×1 struct]
    p_prc: [1x1 struct]
    p_obs: [1x1 struct]
     traj: [1x1 struct]
Ignored trials: none
Irregular trials: none
Optimizing...
Calculating the log-model evidence (LME)...
Results:
Parameter estimates for the perceptual model:
    mu_0: [NaN 0 2.5085]
    sa_0: [NaN 0.1000 2.5638]
    rho: [NaN 0 0]
      ka: [1 1]
      om: [NaN -3.9726 -4.5274]
Parameter estimates for the observation model:
    ze: 4.7457
Model quality:
    LME (more is better): -68.565
    AIC (less is better): 130.7821
    BIC (less is better): 149.6237
    AIC and BIC are approximations to -2*LME = 137.1299.
est4 =
  struct with fields:
        y: [320 \times 1 double]
        u: [320×1 double]
      ign: []
      irr: [0x1 double]
    c_prc: [1×1 struct]
```

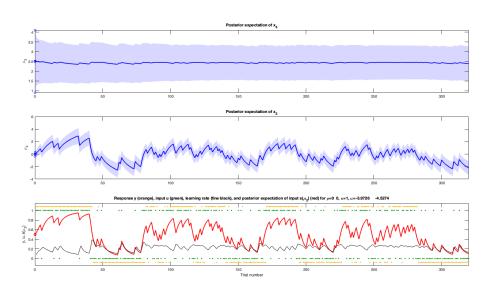
```
c_obs: [1×1 struct]
c_opt: [1×1 struct]
optim: [1×1 struct]
p_prc: [1×1 struct]
p_obs: [1×1 struct]
traj: [1×1 struct]
```











#### c)

%The  $\mu_3$  can only be changed without changing the other beliefs by  $\alpha_3$  or  $\alpha_3$  or  $\alpha_2$ .

### d) tapas\_unitsq\_sgm\_mu3 as response model

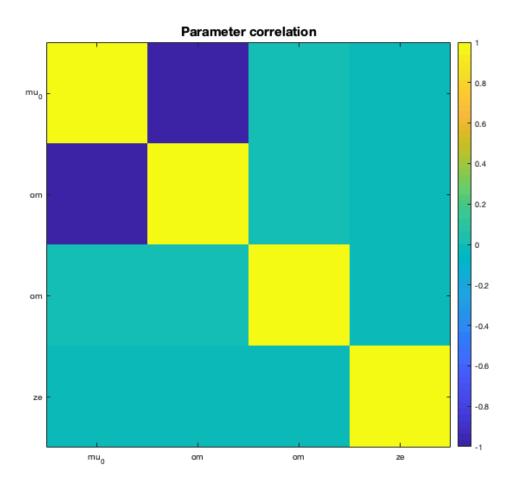
```
%simulate model
sim = tapas_simModel(u,...
'tapas_hgf_binary',...
[NaN 0 1 NaN 1 1 NaN 0 0 1 2.5 NaN -4 -6],...
'tapas_unitsq_sgm',...
5);
%estimate param: (ze,mu3,K2,exp(w3))
est1 = tapas_fitModel(sim.y,...
                     sim.u,...
                     'tapas_hgf_binary_config_2',...
                     'tapas_unitsq_sgm_mu3_config',...
                     'tapas_quasinewton_optim_config')
%plot posterior correlation
tapas_fit_plotCorr(est1)
%plot trajectories
tapas_hgf_binary_plotTraj(est1)
%estimate param: (ze,mu3,w2,exp(w3))
est2 = tapas_fitModel(sim.y,...
                     sim.u,...
                     'tapas_hgf_binary_config_3',...
                     'tapas_unitsq_sgm_mu3_config',...
                     'tapas_quasinewton_optim_config')
%plot posterior correlation
tapas_fit_plotCorr(est2)
%plot trajectories
tapas_hgf_binary_plotTraj(est2)
Ignored trials: none
Ignored trials: none
Irregular trials: none
Optimizing...
Calculating the log-model evidence (LME)...
Results:
```

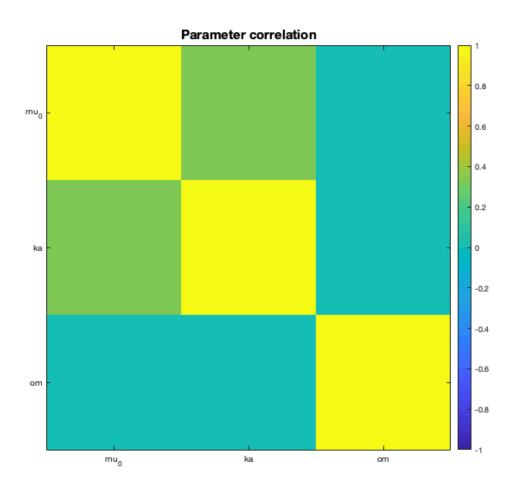
```
Parameter estimates for the perceptual model:
    mu_0: [NaN 0 -1.0744]
    sa 0: [NaN 0.1000 1]
     rho: [NaN 0 0]
      ka: [1 0.3163]
      om: [NaN -4 -5.9786]
Model quality:
    LME (more is better): -150.577
    AIC (less is better): 284.8375
    BIC (less is better): 296.1425
    AIC and BIC are approximations to -2*LME = 301.1539.
est1 =
  struct with fields:
        y: [320 \times 1 double]
        u: [320×1 double]
      ign: []
      irr: [0x1 double]
    c_prc: [1x1 struct]
    c_obs: [1x1 struct]
    c_opt: [1x1 struct]
    optim: [1x1 struct]
    p_prc: [1x1 struct]
    p_obs: [1x1 struct]
     traj: [1x1 struct]
Ignored trials: none
Irregular trials: none
Optimizing...
Calculating the log-model evidence (LME)...
Results:
Parameter estimates for the perceptual model:
    mu_0: [NaN 0 -1.4751]
    sa_0: [NaN 0.1000 1]
     rho: [NaN 0 0]
      ka: [1 1]
      om: [NaN -0.1441 -5.9283]
Model quality:
    LME (more is better): -67.9986
    AIC (less is better): 124.8677
    BIC (less is better): 136.1726
    AIC and BIC are approximations to -2*LME = 135.9972.
```

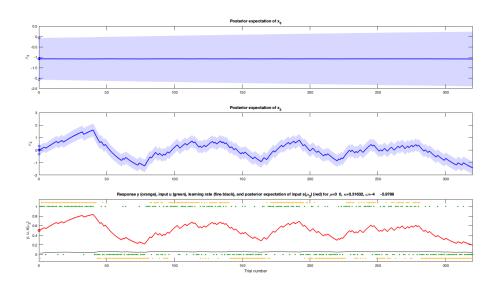
#### est2 =

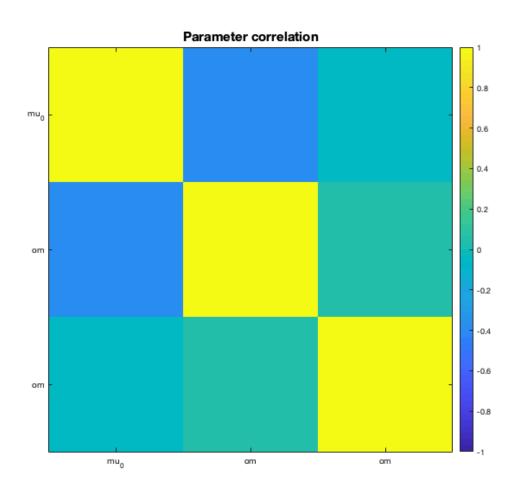
#### struct with fields:

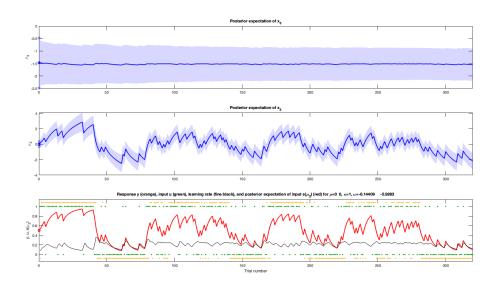
y: [320×1 double]
 u: [320×1 double]
ign: []
irr: [0×1 double]
c\_prc: [1×1 struct]
c\_obs: [1×1 struct]
c\_opt: [1×1 struct]
optim: [1×1 struct]
p\_prc: [1×1 struct]
p\_obs: [1×1 struct]
traj: [1×1 struct]











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